JOURNAL OF MANAGEMENT AND BUSINESS SOLUTIONS

Examining the Effects of Income Inequality, Relative Deprivation in Wages and Education on Health Expenditures in Selected Developing Countries Using the Panel Quantile Method

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ABSTRACT

This study examines the effects of income inequality, relative deprivation in wages, and human capital on health expenditures in selected developing countries over the period 2000–2024. The selected countries were chosen based on the Human Development Index (HDI), with HDI values close to that of Iran. The present research is applied in terms of purpose, analytical-descriptive in nature, and ex post facto in design, and panel quantile regression was employed for the analysis. This method makes it possible to examine the effects of explanatory variables across the entire distribution of health expenditures and mitigates the limitations of conventional linear regression, such as heteroskedasticity and sensitivity to outliers. The dependent variable is government health expenditure, which includes expenditures on prevention, treatment, insurance, and emergency assistance. Income inequality was measured using the Gini coefficient, while relative deprivation in wages and human capital was measured using the Yitzhaki index. In addition, the development of modern technologies, the global COVID-19 crisis, gross fixed capital formation, labor employment, population, and CO_2 emissions were incorporated into the model as control variables. Statistical prerequisites included panel unit root tests and the Kao cointegration test, through which the stationarity of the variables and the existence of a long-run relationship among them were confirmed. The results of panel quantile regression indicate that income inequality and relative deprivation in wages and education have positive and statistically significant effects on health expenditures, with their effects becoming stronger at higher quantiles of the health expenditure distribution. In contrast, the development of modern technologies has a negative and statistically significant effect on health expenditures. The findings indicate that policies aimed at reducing inequality and improving human capital may contribute to more effective management of healthcare costs, while investment in modern technologies can enhance efficiency and reduce financial pressure on the healthcare system.

Keywords: income inequality, relative deprivation, human capital, health expenditures, developing countries, panel quantile regression, modern technologies, cointegration

Introduction

Health expenditure constitutes one of the most important components of public expenditure because the health status of a population directly influences labor productivity, human capital formation, social welfare, economic growth, and the sustainability of development. Over recent decades, healthcare systems in both developed and



Article history:
Received 09 June 2026
Revised 29 July 2026
Accepted 20 September 2026
Initial Publish 24 September 2026
Published online 01 March 2027

How to cite this article:
Safarzadeh, S., Agheli, L. A., & Seyedshokri, K. (2027). Examining the Effects of Income Inequality, Relative Deprivation in Wages and Education on Health Expenditures in Selected Developing Countries Using the Panel Quantile Method. *Journal of Management and Business Solutions, 5*(3), 1-20. https://doi.org/10.61838/jmbs.458

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developing countries have faced increasing financial pressure due to population growth, urbanization, epidemiological transition, rising prevalence of chronic and non-communicable diseases, environmental degradation, technological change, and growing public expectations regarding the quality and accessibility of healthcare services. These pressures are particularly pronounced in developing countries, where governments are often required to expand healthcare coverage despite constrained fiscal resources, unequal income distribution, and substantial socioeconomic disparities. Evidence from Bangladesh, for example, indicates that healthcare costs are shaped not only by economic growth but also by energy use, industrialization, urbanization, environmental quality, and changes in land and forest resources, demonstrating that health expenditures are embedded within a complex system of socioeconomic and environmental determinants (1). Similarly, research on African countries has shown that health expenditures interact with environmental conditions, particularly carbon dioxide emissions, in determining broader dimensions of quality of life, thereby emphasizing the importance of examining healthcare spending in conjunction with demographic, economic, and environmental factors rather than as an isolated fiscal variable (2). Accordingly, understanding the determinants of health expenditure has become a central issue for policymakers seeking to improve population health while maintaining the financial sustainability of healthcare systems.

Income distribution represents one of the fundamental socioeconomic mechanisms through which health outcomes and healthcare expenditures may be affected. Income inequality can influence health through several pathways, including differences in access to preventive and therapeutic care, nutritional quality, living conditions, health literacy, exposure to environmental hazards, and psychological stress. In societies characterized by considerable income inequality, lower-income groups are more likely to postpone medical treatment, experience inadequate preventive care, and face higher risks of chronic illness, which may eventually increase the demand for costly healthcare interventions. At the macroeconomic level, unequal distribution of income can also generate differences in the allocation and utilization of healthcare resources, thereby affecting government health expenditures. The relationship, however, may be bidirectional, because public health expenditure itself can influence inequality by reducing differences in access to essential health services and protecting households against financially catastrophic illness. Studies conducted in selected member states of the Organisation of Islamic Cooperation have specifically examined this interrelationship and documented the importance of health expenditures in explaining variations in income inequality (3). Related evidence likewise highlights the distributive implications of healthcare spending and suggests that the structure and effectiveness of public health expenditure may play an important role in socioeconomic inequality (4). These findings demonstrate that the inequality–health expenditure nexus should not be interpreted merely as a simple linear association; rather, its magnitude may vary substantially across countries and across different levels of healthcare expenditure.

An important concept closely related to income inequality is relative deprivation. Unlike measures of absolute income or poverty, relative deprivation emphasizes an individual's socioeconomic position compared with relevant reference groups. From this perspective, individuals may experience deprivation not only because they lack resources in absolute terms but also because their income, wages, education, or other forms of socioeconomic capital fall below those of comparable individuals. Relative deprivation can consequently generate psychological stress, reduced social participation, unfavorable health behaviors, and diminished access to healthcare resources, all of which may contribute to deteriorating health and greater demand for healthcare services. Wage-related relative deprivation is especially important because wages determine households' ability to finance nutrition, housing,

preventive healthcare, insurance, and medical treatment. Educational deprivation is similarly consequential because education forms an essential component of human capital and strongly affects employment opportunities, income-generating capacity, health literacy, and individuals' ability to understand and use medical information. In this context, household vulnerability to high healthcare costs provides an important illustration of how socioeconomic disparities translate into financial burdens. Evidence from Bangladesh shows that households affected by non-communicable diseases may experience catastrophic health expenditures and adopt coping strategies that can further weaken their economic position, indicating the close relationship between socioeconomic vulnerability, disease burden, and healthcare costs (5). Therefore, simultaneous examination of income inequality and relative deprivation in wages and education provides a more comprehensive framework for understanding socioeconomic pressures on health expenditures than the use of income inequality alone.

At the same time, the determinants of health expenditures are undergoing substantial transformation because healthcare systems are increasingly shaped by emerging technologies. Information and communication technology, artificial intelligence, blockchain, advanced diagnostic tools, digital platforms, electronic health records, telemedicine, smart medical devices, and data-driven decision systems are changing the organization and delivery of healthcare. Emerging technologies can potentially reduce expenditure by improving diagnostic accuracy, facilitating early detection, optimizing resource allocation, reducing administrative inefficiencies, preventing duplication of services, and supporting remote healthcare delivery. Evidence regarding information technology innovation in healthcare indicates that technological performance should be evaluated through multidimensional indicators involving efficiency, quality, accessibility, and organizational outcomes (6). Furthermore, recent assessments of emerging technologies in medical and biological sciences emphasize their expanding applications in diagnosis, treatment, monitoring, and research and their potential to fundamentally reshape clinical and healthcare processes (7). Thus, technological development is increasingly relevant not only to the quality of care but also to the economic structure of healthcare provision.

Artificial intelligence constitutes one of the most prominent components of this technological transformation. AI-based systems can process large volumes of clinical and administrative information, support diagnostic decision-making, predict disease risks, identify patterns in patient records, and facilitate personalized healthcare services. In patient health data management, artificial intelligence may enhance the speed and accuracy of data processing and improve the ability of healthcare providers to use information for clinical and managerial decision-making (8). AI applications in clinical care and treatment are similarly described as a major transformation within contemporary health systems because they can improve diagnostic support, treatment planning, patient monitoring, and the efficiency of healthcare delivery (9). However, adoption of AI also requires investment in infrastructure, data governance, workforce skills, cybersecurity, and institutional redesign. Consequently, technological development may increase expenditures in the short run while generating savings through efficiency gains over longer horizons. This dual effect reinforces the need for empirical models capable of identifying heterogeneous relationships across different levels of health expenditure.

Blockchain technology is another emerging innovation with potential economic implications for healthcare systems. The decentralized and traceable architecture of blockchain may improve transparency, enhance data security, facilitate insurance claims management, and reduce administrative inefficiencies. A model developed for the Iranian health insurance sector suggests that integration of blockchain technology may help reduce hidden healthcare insurance costs by improving the management and verification of transactions (10). Emerging

technologies may also enhance organizational and financial processes beyond direct clinical care. For example, research concerning accounting processes in Iran's healthcare sector emphasizes the potential role of emerging technologies in improving the accuracy, efficiency, and transparency of accounting and financial information systems (11). Such technological innovations are important because inefficiencies in administration, insurance, accounting, procurement, and supply chains can contribute substantially to overall healthcare expenditures even when they are not directly associated with treatment delivery.

Healthcare supply chains are particularly important in this context because modern health systems depend on the reliable procurement and distribution of pharmaceuticals, equipment, medical devices, and other critical resources. The selection of appropriate emerging technologies for healthcare supply chains requires consideration of organizational, technical, economic, and operational factors, and identifying these determinants is essential for successful implementation (12). More generally, emerging technologies can improve healthcare services through better information flows, increased coordination, automation, enhanced accessibility, and more effective use of available resources (13). These developments suggest that technology can influence health expenditure through several mechanisms simultaneously: it may require substantial initial investment while also reducing waste, improving preventive care, lowering transaction costs, and improving resource productivity. The net effect is therefore an empirical question and may differ according to the position of a country or healthcare system within the expenditure distribution.

The relationship between information technology and public-sector health spending has also attracted growing empirical attention. Research involving municipalities in the Brazilian state of Paraná has examined the association between information technology, public management effectiveness, and health expenditure, illustrating that technological capacity and public-sector management performance are closely connected to expenditure patterns (14). At the institutional level, however, accurate measurement of technology-related expenditure remains challenging. A scoping review of hospital information technology expenditures has demonstrated the methodological difficulties involved in making cross-institutional comparisons and emphasized the need for more consistent measurement frameworks for technology spending (15). These findings are important because estimates of the economic consequences of digitalization depend heavily on whether technological expenditures are treated merely as additional costs or evaluated in relation to the efficiency improvements and long-term savings they generate.

The emergence of advanced medical technologies has also intensified debate regarding the balance between innovation and cost containment. New diagnostic technologies may increase initial expenditure but reduce future costs by detecting diseases earlier and facilitating more targeted interventions. For instance, economic analysis of biomarkers and oncoviruses indicates that advanced diagnostic and screening approaches can generate healthcare cost savings by enabling more efficient disease detection and management (16). Likewise, innovations in green flexible electronics are increasingly relevant to modern healthcare ecosystems because flexible and wearable devices can support patient monitoring and potentially facilitate more decentralized and resource-efficient models of healthcare delivery (17). These developments imply that the economic impact of technological progress should not be assessed only in terms of the purchase price of medical technologies but also through their effects on prevention, diagnosis, service delivery, and downstream healthcare utilization.

Sustainability considerations further broaden the relationship between health expenditure and technological development. Healthcare systems consume energy and resources and generate substantial quantities of waste,

creating both economic and environmental externalities. Modern technologies for medical waste management can enhance segregation, treatment, recycling, monitoring, and environmentally sustainable disposal processes and may therefore contribute to both environmental protection and operational efficiency (18). Similarly, the relationship among health expenditure, green finance, and environmental sustainability has attracted attention because health investment and environmental policy may jointly influence sustainable development outcomes. Empirical evidence shows that health expenditures and green finance are relevant to ecological footprint dynamics, highlighting the interconnected nature of public health, environmental quality, and sustainable economic development (19). Consequently, variables such as carbon dioxide emissions should be considered when assessing the determinants of health expenditure, particularly in developing countries where rapid industrialization and urbanization may increase both environmental hazards and the burden placed on healthcare systems.

The expansion of modern healthcare models also highlights the importance of institutional transformation. Contemporary healthcare systems increasingly emphasize integrated service delivery, prevention, digitalization, value-based care, and improved patient experience. Evidence from healthcare leaders in Saudi Arabia indicates that transformation toward a modern healthcare model requires organizational restructuring, stronger integration, technological adoption, and changes in the delivery and governance of health services (20). These transformations may ultimately alter expenditure patterns by shifting resources from traditional hospital-centered treatment toward preventive, integrated, and digitally enabled healthcare. However, the ability of developing countries to realize such benefits may be constrained by unequal access to technology, differences in institutional capacity, infrastructure limitations, and socioeconomic inequalities. Accordingly, the expenditure-reducing effects of modern technology are unlikely to be homogeneous across countries or across different positions within the health expenditure distribution.

The COVID-19 pandemic further demonstrated the vulnerability of healthcare systems to large and unexpected shocks. Governments were required to mobilize extraordinary resources for testing, treatment, vaccination, intensive care capacity, protective equipment, and emergency social and health interventions. The pandemic simultaneously accelerated digital health adoption, telemedicine, remote monitoring, and data-based healthcare management, illustrating the interaction between crisis-induced expenditure and technological innovation. In developing countries, where healthcare resources are comparatively constrained, such shocks can amplify pre-existing inequalities and reveal substantial differences in fiscal capacity and healthcare access. Consequently, controlling for the COVID-19 crisis is necessary when analyzing health expenditures over periods that encompass the pandemic. Likewise, labor employment, capital formation, population dynamics, and urbanization represent important macroeconomic determinants because they influence both the demand for healthcare and governments' capacity to finance health services.

Despite the growing literature on healthcare expenditure, several important analytical gaps remain. A substantial proportion of previous research has focused either on the determinants of average health expenditure or on the effects of health spending on economic, social, or environmental outcomes. Conventional mean-based regression methods, however, may obscure substantial heterogeneity across countries with relatively low, medium, or high health expenditures. The influence of income inequality, wage deprivation, educational deprivation, technological development, environmental pressures, and macroeconomic conditions may differ markedly across the conditional distribution of health expenditure. Such heterogeneity is particularly relevant in developing countries because these countries vary considerably in institutional quality, income distribution, technological infrastructure, demographic

structure, and fiscal capacity. Quantile-based methods provide an appropriate analytical framework because they allow the effects of explanatory variables to be estimated at different points of the conditional health expenditure distribution rather than assuming that a single average coefficient adequately describes all observations.

Moreover, the combined effects of income inequality, relative deprivation, and technological development have received comparatively limited attention. Existing studies underscore the socioeconomic consequences of healthcare expenditure (3), the potential distributive implications of health spending (4), the financial vulnerability associated with catastrophic expenditure (5), and the growing role of information technology and emerging healthcare innovations (14, 15). Technological studies also demonstrate the potential contributions of artificial intelligence (8), blockchain (10), digital innovation (6), advanced diagnostic technologies (16), and sustainable healthcare technologies (17, 18). Nevertheless, analyzing these factors jointly with income inequality and relative deprivation can provide a more comprehensive understanding of why health expenditures vary across developing countries and why their determinants may exert different effects at different expenditure levels.

Such an integrated approach is especially relevant for countries whose levels of human development are comparable but whose socioeconomic structures and healthcare systems differ. By considering selected developing countries with HDI levels close to that of Iran, it becomes possible to examine health expenditure dynamics within a relatively comparable development context while retaining sufficient variation in income distribution, labor markets, human capital, technology adoption, population characteristics, environmental conditions, and healthcare financing. The inclusion of relative deprivation in both wages and education further extends the analysis beyond conventional inequality measures by capturing socioeconomic disparities that may not be reflected fully in the Gini coefficient. At the same time, incorporating information and communication technology development makes it possible to assess whether technological advancement is associated with greater healthcare efficiency and lower expenditure or whether its cost effects vary across the distribution.

Therefore, the aim of the present study is to examine the quantile effects of income inequality, relative deprivation in wages and education, and modern technology development on health expenditures in selected developing countries over the period 2000–2024 using a panel quantile regression approach.

Methods and Materials

The present study examines the effects of income inequality, relative deprivation in wages and education, and health expenditures in selected developing countries using the panel quantile method. In terms of purpose, this study is applied, and in terms of nature, it is analytical-descriptive and falls within the category of ex post facto research. The statistical population consists of selected developing countries for which the required data were available over the period 2000–2024.

The Human Development Index (HDI) was used to select the developing countries, and countries whose HDI values were close to that of Iran were selected as the study countries. In the present research, the Human Development Index was used as the criterion for country selection. The HDI is a relative measure of life expectancy, literacy, the quality and level of education, and, more generally, living standards in human societies. The Human Development Index is estimated by measuring the level of well-being, particularly the welfare of children and younger individuals. Such statistics can be used to assess countries' levels of development and the effects of economic policies on standards of living. Based on this index, the selected developing countries are presented below.

Table 1. Human Development Index (HDI) in the Selected Developing Countries

Country	HDI	Country	HDI
Iran	0.798	Venezuela	0.761
Türkiye	0.791	Brazil	0.759
Serbia	0.787	Azerbaijan	0.757
Georgia	0.780	China	0.757
Mexico	0.774	Colombia	0.747

Following Xiang Xu et al. (2022), Loipersberger et al. (2022), and Wahid et al. (2021), the present study examines the quantile effects of income inequality, relative deprivation, and modern technologies on health expenditures. Quantile regression is a technique capable of overcoming the aforementioned limitations. Introduced by Koenker and Bassett (1978), this model has gradually developed into a comprehensive statistical method for analyzing linear and nonlinear models of response variables in various fields. By applying quantile regression and estimating a family of conditional quantile functions, a more complete representation of the effects of explanatory variables across all parts of the distribution can be obtained.

The principal motivation for employing quantile regression is to provide a precise and comprehensive assessment of the response variable by developing a model in which independent variables can exert effects not only at the center of the data distribution but also across the entire distribution, particularly in the lower and upper tails, without being constrained by the assumptions of conventional regression, heteroskedasticity, or the influential presence of outliers in coefficient estimation. In fact, quantile regression generalizes the concept of an unconditional quantile to a conditional quantile when one or more explanatory variables are present. In contrast to least-squares regression methods, in which conditional mean functions are estimated by minimizing the sum of squared residuals, quantile regression methods estimate conditional median functions and a broad range of other conditional quantile functions by asymmetrically minimizing the weighted absolute values of residuals. In addition to these characteristics, quantile regression is more robust than ordinary least squares in the presence of heteroskedasticity. The model employed in this study is specified as follows:

$$Q\left(HE_{ti}^{DEV} \mid IQ_{1,\dots,n,t}\right) = \rho_{0,q} + \beta_1 IQ_{ti} + \beta_2 WAGEIQ_{ti} + \beta_3 EDUIQ_{ti} + \beta_4 ICT_{ti} + \beta_5 COVID_{ti} + \beta_6 L_{ti} + \beta_7 K_{ti} + \beta_8 POP_{ti} + \beta_9 CO2_{ti} + \varepsilon_{ti}$$

HE_t: Government health expenditures, including total health expenditures allocated to healthcare services (prevention and treatment), households' prospective arrangements for obtaining such services (insurance services), nutrition, and unforeseen emergency assistance. In the present study, government public expenditure on community health is used.

IQ: Income inequality, measured using the Gini coefficient, which is an indicator of inequality in income distribution.

To measure relative deprivation, the Yitzhaki index (Yitzhaki, 1979) is used, including $WAGEIQ$, which represents relative deprivation in wages, and $EDUIQ$, which represents relative deprivation in human capital/education. Statistical data from the University of Maryland are used for these measures.

ICT: Information and Communication Technology Development Index. This index is published by the International Telecommunication Union and consists of three principal components: access, use, and skills. The

index is scored on a scale from zero to ten. A higher score indicates a higher level of ICT development, whereas a lower score indicates a lower level of ICT development in a country.

K: Gross fixed capital formation as a percentage of gross domestic product; L: labor employment; and CO_2: carbon dioxide emissions, used as a measure of air pollution.

POP: Population. The environmental variable used in this study is the urbanization rate, or the proportion of the total population living in urban areas. This variable may potentially have both positive and negative effects on health. On the positive side, urbanization increases health-related information and access to healthcare services. Conversely, in addition to higher healthcare costs in urban areas, urbanization is associated with pollution and congestion, which negatively affect health. Considering both dimensions of urbanization, its ultimate effect on health depends on the net result of these opposing effects.

$COVID$: The global COVID-19 crisis. A value of 1 is assigned to the periods affected by the crisis, while a value of 0 is assigned to the remaining periods.

The hypotheses of the present study are as follows:

Income inequality has a positive and statistically significant effect on health expenditures in selected developing countries.

Relative deprivation has a positive and statistically significant effect on health expenditures in selected developing countries.

Modern technologies have a negative and statistically significant effect on health expenditures in selected developing countries.

Findings and Results

Initially, the stationarity of the research variables is examined to ensure that the variables remain stationary throughout the analysis. When variables are nonstationary, the estimation of econometric models using such variables may result in spurious regression. A substantial number of economic time series are nonstationary, and regressions among them are generally spurious or artificial (Granger & Newbold, 1974). Traditionally, the Dickey–Fuller (DF), Augmented Dickey–Fuller (ADF), and Phillips–Perron (PP) tests have been employed to detect the presence of unit roots in time-series data.

Because panel data incorporate a time dimension, it is appropriate to apply panel unit root tests. Panel unit root tests have been shown to have greater power and accuracy than unit root tests developed for time-series data, such as the DF and ADF tests (Levin & Lin, 1992). Compared with time-series unit root tests, which involve complicated asymptotic distributions, panel unit root tests yield statistics with normal asymptotic distributions (Baltagi, 2005). Among the various panel unit root tests, two widely used procedures are the Levin, Lin, and Chu test, commonly referred to as LLC (Levin et al., 2002), and the Im, Pesaran, and Shin test, commonly referred to as IPS (Im et al., 2003). These tests are based on an Augmented Dickey–Fuller specification. The LLC test is based on a Dickey–Fuller specification of the following form:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + X'_{it}\delta + \varepsilon_{it} \qquad (1)$$

where $i$denotes the cross-sectional unit and $t$denotes the time period. $p_i$represents the number of selected lags used in the ADF test, and X'_{it}represents the vector of exogenous variables in the model. The LLC test assumes that the autoregressive coefficient $(\alpha)$is identical across all cross-sectional units. The null and alternative hypotheses of this unit root test are specified as follows:

$$H_0: \alpha = 0$$

indicating the existence of a unit root, and

$$H_1: \alpha < 0$$

indicating the absence of a unit root.

In summary, the LLC test is based on an indicator equation constructed from disturbance components obtained by estimating the following two auxiliary regressions:

$$\Delta y_{it} = \sum_{j=1}^{p_i} \beta_{ij}\, \Delta y_{it-j} + X'_{it}\delta + e_{it} \qquad (2)$$

$$y_{it-1} = \sum_{j=1}^{p_i} \beta_{ij}\, \Delta y_{it-j} + X'_{it}\delta + V_{it} \qquad (3)$$

The residuals obtained from these equations, namely $\hat{V}_{it}$and $\hat{e}_{it}$, are standardized using the estimated standard deviations, S_i, from the Augmented Dickey–Fuller specification in Equation (1):

$$\tilde{e}_{it} = \frac{\hat{e}_{it}}{S_i} \qquad (4)$$

$$\tilde{V}_{it} = \frac{\hat{V}_{it}}{S_i} \qquad (5)$$

Finally, the indicator equation is formulated as follows:

$$\tilde{e}_{it} = \alpha \tilde{V}_{it} + \eta_{it} \qquad (6)$$

For the estimated value of α, denoted by $\hat{\alpha}$, the LLC procedure generates an adjusted t-statistic that is asymptotically normally distributed under the null hypothesis:

$$t^*_{\alpha} = \frac{t_{\alpha} - \left(N\tilde{T}\right) S_N \hat{\sigma}^{-2} se(\hat{\alpha}) \mu^*_{m\tilde{T}}}{\sigma^*_{m\tilde{T}}} \rightarrow N(0, 1) \qquad (7)$$

where $t_{\alpha}$is the conventional t-statistic, and

$$\tilde{T} = T - \left(\frac{\sum_i p_i}{N}\right) - 1.$$

Furthermore, $\hat{\sigma}^2$denotes the variance obtained from the error component $(\eta)$of the indicator equation, and $se(\hat{\alpha})$denotes the standard error of $\hat{\alpha}$. The relevant adjustment term is defined as:

$$\hat{S}_N = \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\sigma}_{yi}}{\hat{\sigma}_{\varepsilon i}} \qquad (8)$$

where $\hat{\sigma}_{\varepsilon i}$is a kernel estimator of the long-run standard deviation for cross-sectional unit i. The two remaining components, $\mu^*_{m\bar{T}}$and $\sigma^*_{m\bar{T}}$, are adjustment terms for the mean and standard deviation, respectively.

In contrast, the IPS test is based on estimating the following regression:

$$\Delta y_{it} = \alpha_i y_{it-1} + \sum_{j=1}^{p_i}\beta_{ij}\,\Delta y_{it-j} + \mu_{it} \qquad (9)$$

Unlike the LLC test, the IPS test allows the autoregressive coefficients $(\alpha_i)$to vary freely across cross-sectional units. The null hypothesis is expressed as:

$$H_0: \alpha_i = 0 \text{ for all } i$$

whereas the alternative hypothesis may be represented as follows:

$$H_1: \begin{cases} \alpha_i = 0, & i = 1,2,\dots,N_1, \\ \alpha_i < 0, & i = N_1+1, N_1+2, \dots, N, \end{cases} \quad 0 < N_1 \le N \qquad (10)$$

Therefore, when a subset of the cross-sectional units is stationary, the null hypothesis is rejected. Im et al. (2003) effectively conduct separate unit root tests for Nindividual units and subsequently define the t-bar statistic as the simple average of the cross-sectional ADF statistics, t_{iT}. The t-bar statistic used to test the hypothesis $\alpha_i = 0$in Equation (9) can be expressed as:

$$\bar{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT}\,(p_i, \alpha_i) \qquad (11)$$

They assume that the t_{iT}statistics are white noise or independently and identically distributed (i.i.d.).

Before conducting the panel cointegration test to determine the long-run relationship among the principal indicators of the study, the Levin–Lin–Chu (LLC) unit root test is performed.

Table 2. Unit Root Test Results for the Research Variables

Abbreviation	LLC W-statistic	Probability	Stationarity Level
CO_2	-3.191	0.0007	I(0)
COVID	-5.484	0.0000	I(0)
EDUIQ	-1.965	0.0247	I(0)
HE	-5.970	0.0000	I(0)
ICT	-2.723	0.0032	I(0)
IQ	-5.507	0.0000	I(0)
K	-6.895	0.0000	I(0)
L	-11.386	0.0000	I(0)
POP	-3.805	0.0001	I(0)
WAGEIQ	-9.194	0.0000	I(0)

The results presented in Table 2 and the examination of the calculated statistics and their associated probability values indicate that all research variables are stationary at level.

Most economic theories express long-run relationships among variables in levels. To ensure the existence of a long-run relationship among the variables included in a model, the variables must be stationary or, if they are nonstationary, they must have the same order of integration. Therefore, to determine whether a long-run relationship exists among the variables, their stationarity and/or cointegration must be examined using appropriate tests. Accordingly, if the residuals obtained from the estimated regressions are $I(0)$, or stationary, the existence of a long-run relationship among the variables can be established. In the present study, the Kao panel cointegration test was employed to verify the existence of a long-run equilibrium relationship.

Table 3. Results of the Kao Cointegration Test

Test	Test Statistic	Probability
ADF	-5.857654	0.0000

As shown in Table 3, the panel cointegration test conducted among the estimated variables confirms the existence of a relationship among the variables in the estimated regression for the selected developing countries. The hypotheses of the cointegration test are defined as follows:

H_0:No cointegration exists among the variables

H_1:Cointegration exists among the variables

Because the significance level is below 0.05, the null hypothesis asserting the absence of a cointegrating relationship among the variables is rejected. Therefore, the variables are cointegrated in the long run, indicating the existence of a long-run relationship among them.

Various tests are used to determine the optimal model specification for pooled or panel data. One of the most common is the Chow test, which determines whether a panel-data model should be used instead of a pooled-data estimation model.

Suppose the panel linear regression model is expressed as follows:

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_k Z_{kit} + e_{it}$$

where Y_{it}represents the value of the dependent variable for unit $i$in period t, while X_{jit}represents the value of explanatory variable $j$for unit $i$in period t. Differences among cross-sectional units are captured by α_i, which is assumed to remain constant over time. If the null hypothesis assumes that $\alpha_i$is identical across all countries, the OLS method provides efficient and consistent estimates of $\alpha$and β. However, if differences are assumed to exist among the cross-sectional units, the panel-data estimation method is employed. The null and alternative hypotheses are specified as follows:

H_0:The intercept is identical for all cross-sectional units

H_1:At least one cross-sectional unit has a different intercept

To determine whether separate intercepts are required for the individual cross-sectional units, the following F-statistic is used. This procedure represents a simple Chow test:

$$F_0 = \frac{(RRSS - URSS)/(N-1)}{URSS/(NT-N-K)} \sim F_{N-1,\, NT-N-K}$$

In the above equation, $URSS$denotes the unrestricted model, whereas $RRSS$denotes the restricted model with a common constant term for all groups. Kdenotes the number of explanatory variables included in the model, Ndenotes the number of cross-sectional units, and Tdenotes the number of time periods. If the calculated F-statistic exceeds the critical F-value with $N-1$and $NT-N-K$degrees of freedom, the null hypothesis is rejected. Consequently, the restricted regression is not valid, and different intercepts must be incorporated into the estimation. Another fundamental issue is whether the differences in intercepts operate as fixed effects or whether alternative specifications can more clearly capture the differences across individual units. The results of the Limer test are presented in the following table.

Table 4. Results of the Model Selection Test

Test	Test Statistic	Degrees of Freedom	Probability	Selected Model
Limer test	3.326	(9, 231)	0.0008	Panel data
	30.469	9	0.0004	

According to Table 4, because the calculated probability is below 0.05, the null hypothesis that the model should be estimated using the pooled-data method is rejected. Therefore, a panel-data specification is selected for the research model.

In this section, conditional probability distributions of health expenditures are derived through quantile regression, and the effects of the explanatory variables on these distributions are examined. In particular, this section focuses on identifying the effects of income distribution and relative deprivation in wages and education in the lower and upper parts of the health expenditure distribution. The results of the panel quantile estimation are reported in Table 5.

Table 5. Long-Run Coefficient Estimates Using Quantile Regression

Variable	Q-Reg (25) Coefficient (p-value)	Q-Reg (50) Coefficient (p-value)	Q-Reg (75) Coefficient (p-value)	Q-Reg (95) Coefficient (p-value)
C	0.149 (0.0845)	0.534 (0.0715)	0.675 (0.0681)	0.978 (0.0445)
IQ	0.312 (0.0447)	0.498 (0.0358)	0.679 (0.0309)	0.789 (0.0200)
WAGEIQ	0.289 (0.0365)	0.296 (0.0286)	0.653 (0.0201)	0.752 (0.0122)
EDUIQ	0.165 (0.0413)	0.196 (0.0351)	0.278 (0.0239)	0.332 (0.0014)
ICT	-0.256 (0.0337)	-0.653 (0.0201)	-0.712 (0.0197)	-0.824 (0.0007)
COVID	0.196 (0.0289)	0.258 (0.0211)	0.423 (0.0104)	0.668 (0.0020)
L	-0.137 (0.0748)	-0.213 (0.0641)	-0.291 (0.0544)	-0.396 (0.0444)
K	-0.380 (0.0332)	-0.583 (0.0294)	-0.605 (0.0163)	-0.618 (0.0001)
POP	0.105 (0.1597)	0.209 (0.0796)	0.701 (0.0625)	0.942 (0.0418)
CO_2	0.156 (0.0482)	0.205 (0.0365)	0.630 (0.0218)	0.727 (0.0198)

As the results and quantile model estimates in Table 5 indicate, income inequality has a positive and statistically significant effect on health expenditures in the selected developing countries at the first and second, or lower, quantiles, and the magnitude of this effect increases at the third and fourth quantiles. In other words, the income inequality index at the first quantile (Q_{25}) and the second quantile (Q_{50}) exhibits a positive association with health expenditures. As the analysis moves toward the third quantile (Q_{75}) and fourth quantile (Q_{95}), the association between the income inequality index and health expenditures becomes stronger.

Finally, based on the model estimation results, conclusions are drawn and the research hypotheses are tested.

The first hypothesis states that income inequality has a positive and statistically significant effect on health expenditures in selected developing countries. It is reformulated as follows:

H_0:Income inequality has no statistically significant effect on health expenditures in selected developing countries.

H_1:Income inequality has a statistically significant effect on health expenditures in selected developing countries.

According to the calculated probability values for the IQvariable at the first quantile (Q_{25}), second quantile (Q_{50}), third quantile (Q_{75}), and fourth quantile (Q_{95}) in the health expenditure model, all of which are below 0.05, the null hypothesis is rejected. Therefore, the quantile effects of income inequality on health expenditures in selected developing countries are statistically significant. Given the positive coefficient at each quantile, it can be concluded that the first research hypothesis is not rejected at the 95% confidence level.

The second hypothesis states that relative deprivation has a positive and statistically significant effect on health expenditures in selected developing countries. It is reformulated as follows:

H_0:Relative deprivation has no statistically significant effect on health expenditures in selected developing countries.

H_1:Relative deprivation has a statistically significant effect on health expenditures in selected developing countries.

According to the calculated probability values for the $WAGEIQ$and $EDUIQ$variables at the first quantile (Q_{25}), second quantile (Q_{50}), third quantile (Q_{75}), and fourth quantile (Q_{95}) in the health expenditure model, all of which are below 0.05, the null hypothesis is rejected. Therefore, the quantile effects of relative deprivation on health expenditures in selected developing countries are statistically significant. Given the positive coefficients at each quantile, it can be concluded that the second research hypothesis is not rejected at the 95% confidence level.

The third hypothesis states that modern technologies have a negative and statistically significant effect on health expenditures in selected developing countries. It is reformulated as follows:

H_0:Modern technologies have no statistically significant effect on health expenditures in selected developing countries.

H_1:Modern technologies have a statistically significant effect on health expenditures in selected developing countries.

According to the calculated probability values for the ICTvariable at the first quantile (Q_{25}), second quantile (Q_{50}), third quantile (Q_{75}), and fourth quantile (Q_{95}) in the health expenditure model, all of which are below 0.05, the null hypothesis is rejected. Therefore, the quantile effects of modern technologies on health expenditures in selected developing countries are statistically significant. Given the negative coefficient at each quantile, it can be concluded that the third research hypothesis is not rejected at the 95% confidence level.

Discussion and Conclusion

The findings of the present study demonstrate that income inequality, relative deprivation in wages, relative deprivation in education, and technological development are significant determinants of health expenditures in the selected developing countries, although the direction and magnitude of their effects differ across the conditional distribution of health expenditures. The panel quantile estimates showed that income inequality had a positive and statistically significant effect at all examined quantiles, with the magnitude of the coefficient increasing from the lower to the upper quantiles. Specifically, the coefficient of income inequality increased from 0.312 at (Q25) to 0.498 at (Q50), 0.679 at (Q75), and 0.789 at (Q95). This pattern indicates that income inequality exerts a stronger expenditure-increasing effect in countries or observations located at higher levels of the health expenditure distribution. Accordingly, inequality does not appear to affect health expenditure uniformly; rather, its fiscal consequences become more pronounced where healthcare systems are already characterized by relatively high expenditure levels. This result is consistent with the broader literature emphasizing a close relationship between

health expenditure and distributive conditions. Studies examining the relationship between health expenditures and income inequality in selected Organisation of Islamic Cooperation countries have similarly emphasized that health expenditure and income distribution are closely interrelated and that the structure of healthcare financing can have important distributive consequences (3, 4). The present findings extend this line of evidence by showing that the relationship is heterogeneous across quantiles and becomes stronger toward the upper end of the health expenditure distribution.

The positive effect of income inequality on health expenditure can be explained through several complementary mechanisms. Greater inequality can intensify differences in access to preventive healthcare, nutrition, secure housing, insurance coverage, and timely medical treatment. Lower-income groups may delay treatment because of financial constraints, thereby allowing health problems to progress until more expensive forms of care become necessary. At the same time, unequal societies may experience greater prevalence of stress-related conditions, chronic diseases, and social vulnerability, which can increase healthcare utilization and public expenditure. This mechanism is consistent with evidence on catastrophic health expenditure among households affected by non-communicable diseases, where socioeconomic vulnerability is closely associated with financial hardship and the adoption of adverse coping strategies (5). The stronger coefficients at the higher quantiles may therefore indicate that once health systems enter a high-expenditure regime, socioeconomic inequality magnifies existing cost pressures because the marginal health consequences of deprivation require more intensive and costly interventions. This interpretation is also compatible with evidence suggesting that health expenditure is shaped by a broad set of socioeconomic and environmental conditions rather than by healthcare-sector factors alone (1). Thus, the distributional structure of income should be viewed as a central macroeconomic determinant of health-system expenditure.

The results concerning relative deprivation reinforce this interpretation. Relative deprivation in wages had a positive and statistically significant effect on health expenditures at all quantiles, and its coefficient increased markedly from 0.289 at (Q25) to 0.752 at (Q95). Relative deprivation in education also exerted a positive and statistically significant effect, rising from 0.165 at (Q25) to 0.332 at (Q95). These findings indicate that socioeconomic disadvantage is not fully captured by aggregate income inequality alone. Wage deprivation may affect health through reduced purchasing power, unstable employment conditions, constrained access to healthcare, inadequate nutrition, and increased psychological stress. Educational deprivation may affect health by lowering health literacy, reducing the ability to understand medical information, limiting preventive behaviors, and weakening access to more secure employment and higher incomes. The fact that both deprivation measures have larger effects at the upper quantiles suggests that their consequences are cumulative: in settings with already high health expenditures, socioeconomic disadvantage may interact with chronic disease burden, demographic pressures, and institutional inefficiencies to intensify public health costs. This pattern is compatible with the broader argument that healthcare expenditures are shaped by multidimensional determinants of quality of life and environmental conditions rather than by income alone (2). It also supports the view that public health policies should address not merely absolute poverty but also relative socioeconomic disparities that influence exposure to health risks and access to health-enhancing resources.

Another major finding of the study is that ICT development has a negative and statistically significant effect on health expenditures across all quantiles, with the absolute magnitude of the coefficient increasing from (-0.256) at (Q25) to (-0.824) at (Q95). This result suggests that technological development is associated with lower health

expenditures, and that the potential cost-reducing effect of technology becomes stronger at higher levels of health spending. One plausible explanation is that information and communication technologies improve efficiency in healthcare delivery by reducing administrative duplication, improving patient-data management, supporting telemedicine, facilitating early diagnosis, strengthening supply-chain coordination, and improving allocation of scarce resources. The finding is consistent with studies highlighting the contribution of information technology to public management effectiveness and healthcare expenditure patterns (14). It also aligns with research showing that healthcare information technology should be understood as an investment that can affect institutional efficiency, although measuring and comparing hospital IT expenditures remains methodologically challenging (15). Therefore, the negative coefficient found in the present study may reflect the longer-term efficiency gains produced by digitalization rather than simply lower technology spending.

The findings regarding ICT are also supported by the growing literature on emerging healthcare technologies. Research on artificial intelligence has emphasized its potential to improve patient-data management, accelerate information processing, and strengthen clinical and managerial decision-making (8). Similar arguments have been made regarding the transformative role of artificial intelligence in clinical care and treatment, particularly through improvements in diagnosis, monitoring, and personalized care (9). Emerging technologies have also been linked to improvements in healthcare service quality and efficiency more broadly (13). From an expenditure perspective, these technologies may reduce costs through earlier intervention, more accurate diagnosis, reduction of unnecessary procedures, automation of repetitive administrative activities, and better use of human and material resources. The stronger negative ICT coefficient at higher quantiles is particularly important because it suggests that technological adoption may yield the greatest expenditure-saving benefits precisely in settings where healthcare costs are already high. In other words, technology may have a stronger marginal efficiency effect in relatively expensive health systems because these systems offer more opportunities for eliminating duplication, inefficiency, administrative waste, and preventable utilization.

The technological interpretation is further reinforced by evidence regarding blockchain, accounting systems, and healthcare supply chains. Blockchain-based solutions have been proposed as a means of reducing hidden health-insurance costs by improving transparency, traceability, and transaction management (10). Emerging technologies may also improve accounting processes in healthcare organizations, thereby strengthening financial control and reducing information asymmetry and administrative inefficiency (11). In addition, identifying appropriate technologies for healthcare supply chains has become increasingly important because technology selection can affect procurement, inventory management, distribution efficiency, and service continuity (12). These mechanisms provide a plausible explanation for the negative association between ICT development and health expenditure observed in the present study. When digital technologies improve not only clinical processes but also financial, administrative, and logistical processes, their cumulative effect may be a reduction in the cost burden of healthcare delivery.

The results also showed that the COVID-19 variable had a positive and statistically significant effect on health expenditures at all quantiles, with its coefficient rising from 0.196 at (Q25) to 0.668 at (Q95). This result is consistent with the exceptional fiscal and operational burden imposed by the pandemic on health systems. During the crisis, governments were required to finance testing, hospitalization, intensive care, vaccination, protective equipment, emergency staffing, and expanded public health infrastructure. The larger coefficient at higher quantiles suggests that systems already operating at high expenditure levels experienced greater additional fiscal pressure during the

pandemic. At the same time, the pandemic accelerated adoption of digital healthcare technologies, which may partly explain why technological development displays a cost-reducing effect over the broader period. The coexistence of a positive COVID effect and a negative ICT effect therefore reflects two parallel dynamics: the pandemic increased demand and emergency spending, while technological development may have improved the efficiency with which health services were delivered.

The coefficient of gross fixed capital formation was negative and statistically significant at all quantiles, with the effect becoming somewhat stronger at higher quantiles. This finding may indicate that greater capital formation improves infrastructure, productive capacity, and economic efficiency in ways that indirectly reduce the burden on public healthcare expenditure. Improved infrastructure can enhance access to clean water, transportation, housing, sanitation, digital connectivity, and other determinants of health, thereby reducing preventable illness and lowering pressure on healthcare systems. Capital investment may also increase the efficiency of health facilities by modernizing equipment and physical infrastructure. Although the reference literature supplied for this study does not focus directly on gross fixed capital formation, the broader literature on technological modernization supports the idea that investment in more efficient systems and technologies can reduce long-term operating costs (17). The relevance of sustainable technology and infrastructure is further reflected in studies emphasizing the role of modern waste-management technologies in improving environmental and operational performance in healthcare systems (18).

Labor employment displayed a negative coefficient across all quantiles, although statistical significance was achieved only at the highest quantile. This pattern suggests that greater employment may reduce health expenditure pressures by improving household income, insurance coverage, socioeconomic security, and access to preventive services. Employment may also reduce the public fiscal burden by shifting some healthcare financing toward employer-based or contributory mechanisms. However, the relatively weak significance at the lower quantiles indicates that the relationship is not uniform and may depend on labor-market structure, informality, job quality, and the extent to which employment provides effective financial protection. In developing countries, where informal employment is widespread, increases in employment do not necessarily translate into comprehensive health insurance coverage or improved health security. Therefore, the negative relationship observed in this study should be interpreted as conditional rather than universal.

Population and urbanization also showed positive coefficients, although the effects became statistically significant only at the upper quantile. This finding suggests that demographic and urban pressures are particularly important in high-expenditure health systems. Urbanization can increase access to healthcare and improve the availability of medical services, but it can also raise healthcare costs by increasing service utilization, population density, pollution exposure, traffic injuries, and the burden of non-communicable diseases. The positive result is compatible with evidence that urbanization, economic activity, environmental quality, and healthcare costs are closely interconnected (1). In addition, the relationship between health expenditure and environmental sustainability has been emphasized in research examining the role of healthcare spending in ecological outcomes (19). Thus, the positive population effect at higher quantiles may indicate that demographic concentration creates cost pressures that become particularly visible when health systems already operate at relatively high levels of expenditure.

CO(*2) emissions had a positive and statistically significant effect at all quantiles, with the coefficient increasing from 0.156 at (Q*25) to 0.727 at (Q95). This result indicates that environmental degradation is associated with greater health expenditure and that its effect is considerably stronger in the upper part of the expenditure

distribution. Higher CO(_2) emissions are often associated with industrialization, energy consumption, traffic congestion, and air pollution, which contribute to respiratory disease, cardiovascular illness, and other environmentally related health conditions. Consequently, worsening environmental quality can increase healthcare utilization and treatment costs. This finding is strongly consistent with studies showing that CO(_2) emissions moderate the relationship between health expenditure and quality of life (2). It also corresponds with evidence that healthcare costs are influenced by environmental quality, industrialization, energy use, and urbanization (1). The increasing coefficient across quantiles suggests that environmental deterioration may impose especially large fiscal costs in systems already facing substantial health expenditures.

The environmental implications of the findings are also consistent with studies linking health expenditure, green finance, and ecological sustainability (19). Modern healthcare systems are themselves resource-intensive, and therefore sustainability-oriented technological innovation may reduce both environmental and economic pressures. New technologies for medical-waste management, for example, can improve disposal efficiency and reduce environmental externalities (18). Similarly, developments in green flexible electronics and wearable technologies may support remote monitoring and decentralized healthcare, potentially reducing both resource use and service-delivery costs (17). Advanced biomarkers and oncovirus-based diagnostic approaches may also reduce healthcare costs through earlier detection and more targeted intervention (16). These studies reinforce the present finding that technological progress can help mitigate health expenditure pressures, particularly when innovation contributes simultaneously to clinical efficiency and environmental sustainability.

Overall, the results indicate that the determinants of health expenditure are heterogeneous across the expenditure distribution. The positive effects of income inequality, relative deprivation, COVID-19, population, and CO(_2) emissions generally become stronger at higher quantiles, while the negative effect of ICT development also intensifies in absolute magnitude. This pattern provides strong justification for the use of panel quantile regression because a conventional mean-based model would obscure substantial variation in the strength of these relationships. The findings suggest that countries with high levels of health expenditure are particularly sensitive to socioeconomic inequality, deprivation, demographic pressure, environmental degradation, and crisis conditions, while at the same time they may obtain comparatively greater expenditure-saving benefits from technological development. The results therefore support an integrated interpretation of health expenditure in which socioeconomic distribution, human capital, environmental conditions, technological capacity, and institutional efficiency jointly determine fiscal pressures on healthcare systems. This interpretation is compatible with contemporary healthcare transformation models emphasizing technology, integrated service delivery, and institutional modernization (20), as well as research emphasizing key performance indicators for information technology innovation in healthcare (6). Taken together, the evidence suggests that controlling health expenditure in developing countries requires more than conventional budgetary restraint; it requires structural policies that reduce socioeconomic disparities, strengthen human capital, improve environmental quality, and promote effective adoption of cost-saving technologies.

The present study has several limitations. First, the analysis is based on macro-level panel data, which limits the ability to capture household-level and individual-level mechanisms underlying the relationship among inequality, deprivation, technology, and health expenditure. Second, the availability and comparability of data across developing countries may differ, particularly for technological indicators and measures of relative deprivation. Third, the ICT index provides a broad measure of technological development and does not separately identify the effects

of artificial intelligence, telemedicine, blockchain, electronic health records, or other specific technologies. Fourth, the model focuses on selected developing countries with human development levels relatively close to Iran, which may limit the generalizability of the findings to low-income countries or highly developed economies. Fifth, although panel quantile regression captures heterogeneity across the expenditure distribution, the study does not explicitly model possible nonlinear thresholds, structural breaks, cross-sectional dependence, or dynamic feedback effects among the variables.

Future research can extend the present analysis in several directions. Researchers may employ dynamic panel quantile models to investigate persistence in health expenditure and possible lagged effects of inequality and technological development. Future studies may also separate public, private, and out-of-pocket health expenditures to determine whether the identified relationships differ across financing mechanisms. More detailed technological indicators could be incorporated to distinguish the effects of artificial intelligence, digital health platforms, blockchain, telemedicine, wearable technologies, and electronic health records. It would also be useful to examine whether institutional quality, health insurance coverage, governance effectiveness, or the degree of labor-market informality moderates the effects identified in this study. Comparative analyses among different development groups could determine whether the magnitude and direction of the relationships vary systematically according to income level or health-system structure. Finally, future research could combine macroeconomic panel analysis with household-level microdata to clarify the pathways through which socioeconomic deprivation translates into higher healthcare utilization and expenditure.

From a practical perspective, policymakers should consider health expenditure management as a multidimensional policy issue rather than merely a budgeting problem. Policies aimed at reducing income inequality, improving wage conditions, and expanding access to education may contribute indirectly to controlling long-term healthcare costs by reducing preventable health risks and improving access to timely care. Governments should also prioritize investments in digital health infrastructure, interoperable information systems, telemedicine, artificial intelligence, and other technologies that improve resource allocation and administrative efficiency. Environmental policies designed to reduce air pollution and carbon emissions should be coordinated with health policy because environmental deterioration can create substantial additional healthcare costs. At the same time, public investment in preventive care, workforce participation, urban health infrastructure, and technology-enabled service delivery should be targeted particularly toward countries or regions with already high levels of health expenditure, where the results indicate that both socioeconomic risks and potential technological efficiency gains are greatest.

Acknowledgments

We would like to express our appreciation and gratitude to all those who helped us carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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